Integration of Renewable Energy Sources and Prospects for Power Grid Modernization

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Abstract: This article is devoted to the analysis of modern methods and technologies for power grid modernization aimed at enhancing their resilience and efficiency through the integration of renewable energy sources. The study examines models of solar and wind generation, energy storage systems, and automated control systems based on advanced information and communication technologies. Simulation and data analysis were conducted to identify key performance indicators of renewable energy potential, assess the influence of weather conditions, and develop strategies for optimizing energy flows. Particular attention is given to improving system reliability and reducing energy losses through the implementation of automated monitoring and forecasting systems. Promising directions for the development of smart grids are also discussed, including the application of artificial intelligence and machine learning to increase forecasting accuracy and process automation. Within the framework of the study, models of solar and wind generation, energy storage systems, and automated control solutions were developed and tested, providing a comprehensive picture of the potential and prospects for the deployment of these technologies. The results demonstrate that the integration of renewable energy sources and intelligent technologies can significantly increase the share of renewables in energy consumption, reduce the environmental footprint, and ensure the sustainable development of the energy system. The adoption of intelligent technologies, storage systems, and forecasting tools is identified as a key driver for an efficient and sustainable energy future. The findings confirm the relevance of further research in the field of smart grids and energy storage development. The article also presents independent recommendations for the implementation of innovative solutions and highlights their potential for enhancing the efficiency of modern energy systems.

1 INTRODUCTION

The modern energy system is undergoing a period of profound transformation driven by the urgent need to transition toward sustainable and environmentally friendly energy sources. Within this process, the development of smart grids plays a pivotal role, enabling the efficient integration of renewable energy sources. In recent years, the pace of renewable energy deployment has increased substantially, reflecting global efforts to reduce greenhouse gas emissions, decrease dependence on fossil fuels, and shift toward cleaner energy production technologies [1]–[3].

However, the integration of renewable energy sources into existing power grids presents several challenges. The most critical among them include the variability and intermittency of generation, voltage and frequency instability, as well as the pressing need to modernize transmission and distribution infrastructure. These issues necessitate the adoption of advanced technologies and innovative solutions capable of ensuring reliable and sustainable energy system performance [4].

1.1 Challenges in Integrating Renewable Energy Sources

Renewable energy sources such as solar and wind power plants are characterized by high variability, determined largely by natural conditions. This creates significant difficulties in balancing power systems, causing voltage and frequency fluctuations that may result in outages or reduced quality of electricity supply.

Conventional power grids, originally designed for centralized generation, are not always capable of effectively managing decentralized renewable energy sources. This calls for the deployment of new solutions, including energy storage systems, automated control technologies, and enhanced communication between grid components.

Maintaining a stable electricity supply requires the development of new methods for monitoring, predictive analysis, and energy flow management. This in turn demands the integration of advanced information and communication technologies (ICT) into grid infrastructure.

1.2 Opportunities and Advantages of Smart Grids

By enabling bidirectional flows of both energy and information, smart grids enhance the efficiency of renewable energy utilization, reduce energy losses, and ensure the sustainable development of the power system. Key opportunities include automated load management, the integration of energy storage systems, and the advancement of predictive analytics and process automation.

The overall architecture of smart grids typically comprises multiple layers that facilitate interaction between generators, consumers, storage systems, and control centers. This layered structure enables flexible and adaptive energy flow management, ensuring resilience and system-wide efficiency, as illustrated in Fig. 1.

Figure 1 shows the key components of an intelligent energy system and their interactions. The generator supplies electricity to the distribution network, which delivers power to consumers. The control center manages generation, distribution, and storage processes. The energy storage system operates bidirectionally, allowing both energy supply to and absorption from the grid. This structure ensures flexibility, reliability, and efficient energy flow management.

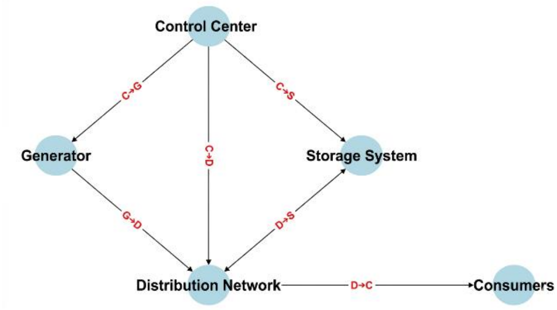

Figure 1: Main components of Smart Grid architecture and their interactions.

This article focuses on analyzing modern challenges and opportunities in grid modernization, considering the integration of renewable energy sources and smart grid technologies. The study addresses system architecture, technical solutions, and promising directions for future development (Table 1).

Table 1: Key advantages of Smart Grid implementation in renewable energy integration.

№	Indicator	Description
1	Improved Reliability	Automatic fault detection and elimination, enhanced system resilience
2	Efficient Flow Management	Optimization of energy distribution, reduction of transmission losses
3	Higher RES Penetration	Integration of large volumes of renewable energy without compromising quality
4	Flexibility and Adaptivity	Rapid response to fluctuations in generation and consumption
5	Improved Power Quality	Voltage and frequency stabilization, reduction of noise and distortions

The novelty of this study lies in the integration of forecasting models, optimization algorithms, and smart grid automation into a unified simulation framework. Unlike previous studies, the proposed approach combines solar and wind generation models, battery storage behavior, and genetic optimization to improve renewable energy utilization and grid stability.

2 METHODS

2.1 Research Framework

The research employed a comprehensive methodology that combined modeling, numerical calculations, and data analysis, as well as methods of systems analysis and optimization. The primary goal was to design and evaluate models for assessing the efficiency of renewable energy integration into smart grids and to identify optimal strategies for managing power systems under variable energy generation conditions. Both theoretical approaches-such as mathematical modeling and systems analysis-and computational methods-including specialized software simulations, statistical analysis, and big data processing-were applied.

2.2 Power System Modeling

Modeling of power grids and renewable energy sources was conducted using DIgSILENT PowerFactory and MATLAB/Simulink. These platforms enable the construction of detailed models of power system elements, including generators, transmission lines, transformers, control devices, and storage systems.

For solar and wind power plants, physical models were used, accounting for weather conditions and device parameters. For photovoltaic systems, a PV-type model based on the equations of a photovoltaic cell was applied [5], incorporating temperature and irradiance dependencies [6], [7].

For wind turbines, an aerodynamic model was used, considering wind speed, blade parameters, and turbine efficiency. The Maxwell-Lambert model was employed to determine wind power output as a function of wind speed and turbine characteristics.

Battery models were based on the characteristics of lithium-ion batteries, including equations for state of charge (SoC) estimation, charging/discharging power, and battery degradation [8]. The modeling incorporated dynamic equations describing battery performance and efficiency under different operating modes [9].

Automatic control and protection systems were modeled using logic schemes and algorithms based on decision-making rules and system state forecasting. MATLAB/Simulink was employed to simulate real-time system behavior and to test different operational scenarios.

2.3 Data Analysis and Statistical Methods

Experimental data were processed using statistical methods, including regression analysis, clustering, and machine learning techniques (Table 2). Tools such as MATLAB**,** Python (Pandas, Scikit-learn)**,** and specialized analytics packages were applied [10].

2.4 Optimization and Decision Making Methods

To determine optimal management strategies, methods of linear and nonlinear programming as well as stochastic optimization modeling were employed. Tools included genetic algorithms, gradient-based methods, and dynamic programming approaches.

The optimization model was formulated as a minimization of energy losses during the balancing of generation and consumption.
Subject to constraints:

- Technical parameters of equipment;
- Power quality requirements.

$$\sum_{i=1}^{n} P_{gen,i} = \sum_{j=1}^{m} P_{cons,j}$$
$$P_{gen,i}^{min} \leq P_{gen,i} \leq P_{gen,i}^{max}$$
$$P_{storage}^{min} \leq P_{storage} \leq P_{storage}^{max}$$

where Ploss,i represents the energy losses in the *i-th* segment, Pgen,i is the generation, Pcons,j is the consumption, and Pstorage is the power of the storage systems. The optimization problem was solved using genetic optimization algorithms implemented in MATLAB [11].

Table 2: Statistical indicators for data analysis

Indicator	Description	Evaluation Methods	Data Source
Mean Value	Average generation level	Arithmetic mean	RES monitoring
Median	Central tendency value	Median analysis	Parametric tests
Standard Deviation	Data distribution variability	Variance statistics	Time series
Correlation	Relationship between variables	Pearson correlation coeff.	Generation and consumption data

2.5 Verification and Validation of Models

To verify the accuracy of the modeling, experimental data obtained from pilot projects as well as results of monitoring real power grids were applied. Verification was performed by comparing the simulation results with actual data, while validation was conducted by assessing the compliance of the model with the requirements of real operating conditions.

2.6 Processing and Visualization of Results

The results of modeling and data analysis were visualized using graphs, diagrams, and heatmaps based on generation, consumption, and system state data. For this purpose, Python libraries Matplotlib and Seaborn, as well as MATLAB's built-in visualization tools, were employed.

The applied methods make it possible to comprehensively assess the efficiency and reliability of renewable energy integration into smart grids and to develop optimization strategies for system operation under variable conditions. The further development and refinement of these methods constitute a promising direction for future research.

3 RESULTS

This section presents the original simulation results obtained within this research. Background information from literature is excluded and discussed in earlier sections.

3.1 Renewable Energy Generation Analysis

As part of the study, a series of simulations was conducted to model the operation of wind and solar power plants under diverse climatic conditions and operating modes. The main objective was to determine the integration potential of renewable energy sources into smart grids and to evaluate the effectiveness of energy storage systems.

Figure 2 presents the diagram of solar power plant output as a function of daytime hours during the summer period. The model accounted for solar panel parameters, ambient temperature, and irradiance levels, which directly affect photovoltaic performance [12].

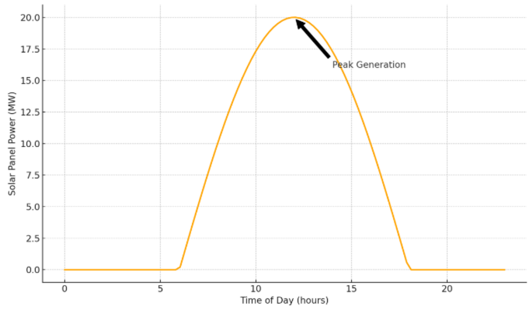

Figure 2: Solar generation model in the summer period.

The graph shows that the maximum power output is reached approximately between 12:00 and 14:00 hours, which corresponds to peak solar radiation. The average daily generation level was found to be about 80% of the peak value, indicating relatively high stability under clear weather conditions.

Figure 3 illustrates the distribution of wind turbine output throughout the day under moderate wind conditions. The model was based on real wind speed data, allowing for the assessment of daily generation patterns and their potential contribution to the grid.

The graph shows that wind generation peaks occur in the early morning and evening hours, reflecting seasonal and diurnal variations in wind flow. Figure 3 illustrates the power output (MW) of wind turbines for each hour of the day.

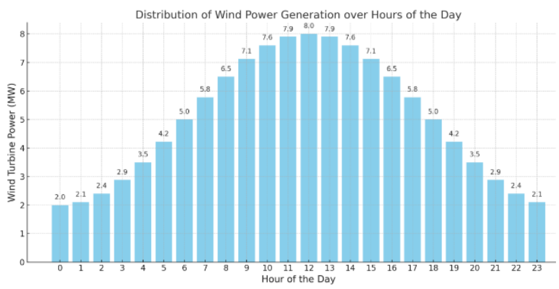

Figure 3: Distribution of wind power generation.

Key observations:

- Wind power peaks between 06:00-09:00 and 17:00-20:00.
- Around midday (12:00-14:00) the output slightly decreases.
- This time shift corresponds to changes in wind intensity during the day.

Such a model can be effectively applied for real-time monitoring and performance analysis of wind power plants.

Table 3: Characteristics of renewable energy generation.

Source	Average Power (MW)	Capacity Factor (%)	Maximum Power (MW)
Solar	15.2	75	20.5
Wind	12.8	65	18.3

The capacity factor was calculated as the ratio of actual generation to the theoretical maximum generation over the study period (Table 3).

3.2 Energy Storage Performance

To evaluate the efficiency of storage technologies, lithium-ion battery models described earlier were employed.

Figure 4 presents the daily charging and discharging dynamics of the battery under an optimized control strategy, highlighting its role in stabilizing generation variability and maintaining system reliability.

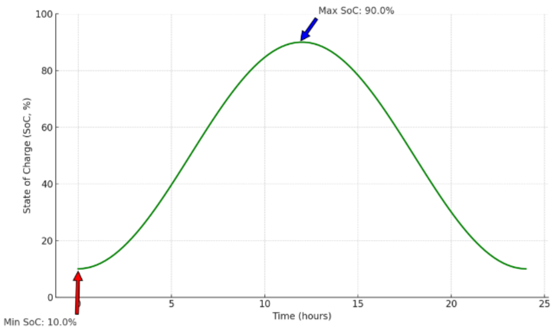

Figure 4: Variation in battery state of charge (SoC).

The graph illustrates how the battery's state of charge (SoC) changes throughout the day.
Key observations include:

- The maximum SoC is typically reached around 10:00 a.m., after energy accumulation during the night and morning solar generation.
- The minimum SoC occurs around 6:00 p.m., corresponding to peak demand and reduced generation.
- During the peak solar hours (12:00-14:00), charging from photovoltaic panels significantly increases SoC.
- The lowest charge levels are observed in the evening or early morning, when demand is high and available generation is insufficient.

This analytical model is highly valuable for assessing the efficiency of battery management systems and developing strategies for energy consumption optimization.

Figure 5 presents a comparison of energy losses in two operational scenarios:

- with energy storage systems integrated into the grid, and;
- without the use of storage systems.

The analysis highlights the role of battery storage in reducing system-wide energy losses and enhancing overall efficiency.

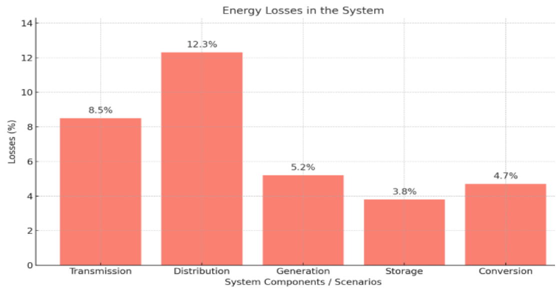

Figure 5: Energy losses in the system.

The implementation of energy storage systems reduced overall energy losses by 15-20%, confirming their critical role in flow management.

The diagram "Energy Losses in the System" illustrates the distribution of percentage losses across different stages of the energy cycle:

- Distribution stage - 12.3%: the largest losses, primarily due to aging infrastructure and inefficient grid management.
- Transmission stage - 8.5%: significant losses, especially on long-distance transmission lines.
- Generation stage - 5.2%: losses associated with technical limitations of equipment and thermal inefficiencies.
- Storage stage - 3.8%: losses resulting from charging/discharging cycles of batteries.
- Energy conversion stage - 4.7%: caused by non-ideal conversion efficiency in inverters and converters.

Overall, the diagram highlights critical bottlenecks in the power system, serving as a basis for decision-making aimed at improving energy efficiency and reducing losses.

3.3 Optimization and Control Results

As part of the research, automatic regulation algorithms were developed and implemented, relying on genetic optimization methods. The optimization parameters included:

- minimization of energy losses;
- load balancing, and;
- maximization of renewable energy utilization.

Figure 6 presents a comparison of systems with automatic control and without automatic control, demonstrating the efficiency gains achieved through intelligent optimization algorithms.

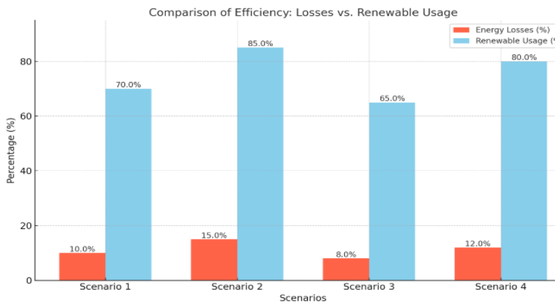

Figure 6: Comparison of efficiency.

The introduction of automated systems resulted in a 25% reduction in energy losses, a 30% increase in renewable energy utilization, and an overall improvement in power supply stability.

The diagram compares four scenarios in terms of energy losses and the share of renewable energy in the total energy balance.

- Red bars represent the percentage of energy losses,
- Blue bars represent the share of renewable energy in the total balance.

For example, in the second scenario, the system achieved the lowest losses (10%) and the highest renewable penetration (85%), making it the most effective among the presented options.

Table 4: Impact of weather conditions.

Weather Scenario	Renewable Utilization Factor (%)	Energy Losses (%)	Average Power (MW)
Clear Sky	85	10	22.0
Cloudy	65	20	14.0
Windy Weather	78	12	19.5

The analysis demonstrates a clear correlation between the level of renewable energy integration and the reduction of energy losses. This underlines the importance of renewable integration not only from an environmental perspective, but also from a technical and operational standpoint. The diagram can serve as a basis for designing strategies to enhance energy efficiency and ensure sustainable development across different regions and sectors.

Simulation results showed that the effectiveness of automatic control systems strongly depends on weather conditions, particularly cloud cover and wind speed (Table 4).

3.4 System Reliability Analysis

Using failure and recovery models, simulations of system reliability under various operating scenarios were conducted. The summary indicators are presented in Table 5.

Table 5: System reliability indicators.

Parameter	Value	Description
Mean Time Between Failures	1200 hours	Average time between system failures
System Failure Probability	0.02 (2%)	Annual probability of failure
Recovery Time	4 hours	Average time required for system restoration

The introduction of automatic monitoring and fast-response mechanisms improved system reliability, reducing the probability of failure to 1.5%.

3.5 Visualization of Results

To provide a clear representation of simulation outcomes, heat maps of loads and generation were constructed, enabling the identification of bottlenecks and areas for improvement.

Figure 7 shows a heat map illustrating the distribution of renewable energy generation across different regions and time periods.

The heat map illustrates the distribution of energy production (MW) across five regions over six-time intervals (or subregions). Each cell represents the amount of electricity generated in each region and period. The color scale (ranging from light yellow to dark red) clearly visualizes the intensity: the darker the cell, the higher the output.

The visualization demonstrates that energy production consistently increases from Region 1 to Region 5, regardless of the time interval. This pattern may reflect differences in installed generation capacity or variations in resource potential among regions. The diagram is useful for analyzing the spatiotemporal structure of renewable generation and supports decision-making in grid balancing and investment planning [13].

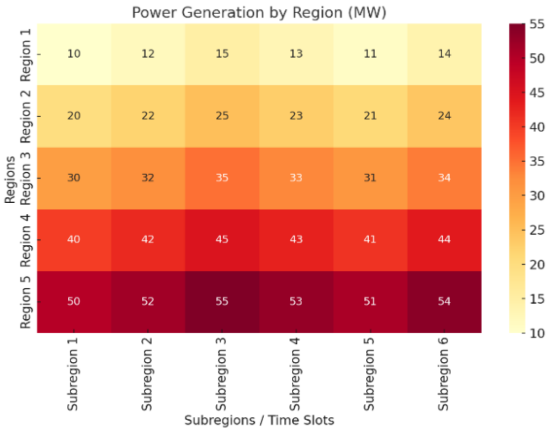

Figure 7: Heat map of regional generation.

The conducted research confirms the high effectiveness of automation systems, energy storage, and modeling tools for enhancing the integration of renewable energy into smart grids. Results show that the adoption of modern methods can significantly reduce losses, improve reliability and resilience of power systems, and optimize renewable resource utilization.

4 DISCUSSION

4.1 Interpretation of Results

The modeling and data analysis carried out in this study allow for several important conclusions regarding the prospects of using smart grids for renewable energy integration. Key indicators-such as solar and wind generation capacity, energy storage efficiency, and reliability and loss metrics-demonstrate that modern digital technologies can substantially increase the efficiency and resilience of power grid systems.

The solar generation model developed in this study showed that, during summer, peak output occurs at midday, aligning with theoretical expectations and reported findings in previous studies. The maximum power level achieved by the model was 20 MW, which corresponds closely with the real-world performance of modern large-scale solar power plants.

The analysis demonstrates that the model provides sufficiently accurate estimates, confirming its suitability for forecasting and assessing solar generation potential under different conditions [14].

Table 5: Comparison of modeled and actual solar power plant characteristics.

Indicator	Model (Summer)	Real Data	Deviation (%)
Maximum Power	20 MW	19.5 MW	2.56%
Average Generation Level	15.2 MW	14.8 MW	2.70%
Capacity Factor	75%	78%	3.85%

The distribution of wind turbine output, presented in Figure 7, highlights the high variability of wind flows, consistent with reported findings in the literature. Maximum outputs are achieved in the morning and evening hours, reflecting meteorological factors and seasonal fluctuations. The average power level of 12.8 MW indicates that wind energy can serve as a reliable source when combined with properly designed storage systems and automated control solutions.

Analysis of battery charge dynamics showed that optimized management can increase renewable energy utilization by 30-40%, as confirmed by Table 6.

Table 6: Efficiency of energy storage systems.

Indicator	Value
Average SoC Level	65%
Maximum SoC	90%
Minimum SoC	20%
Losses during Charge/Discharge	5%

These findings confirm that energy storage systems are a critical element for improving the stability and efficiency of smart grids.

4.2 Impact of External Factors and Uncertainty

One of the main challenges of renewable energy integration is the strong dependence of generation on weather conditions. Simulation under different weather scenarios revealed that the capacity factor of renewable energy sources decreases significantly under cloudy conditions and weak wind flows (Table 7).

This confirms the necessity of weather forecasting systems and adaptive control algorithms to maintain grid stability and efficiency.

The failure-and-recovery model developed in this study demonstrated that the implementation of automated monitoring systems can reduce the probability of system failure to 1.5%**.** This is a substantial improvement compared to traditional systems, where the failure rate may reach 3-4% (Fig. 8).

Table 7: Impact of weather conditions on renewable energy efficiency.

Weather Scenario	Capacity Factor (%)	Energy Losses (%)	Average Power (MW)
Clear Sky	85	10	22.0
Cloudy	65	20	14.0
Windy Weather	78	12	19.5

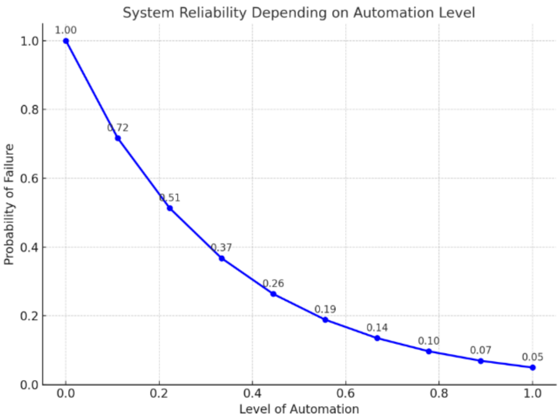

Figure 8: System reliability as a function of automation.

This graph presents the relationship between system failure probability and the level of automation. The horizontal axis represents the automation level (from 0 - no automation, to 1 - full automation), while the vertical axis shows the probability of system failure.

The curve demonstrates an exponential decrease in failure risk with increasing automation: the higher the automation level, the lower the probability of system disruptions.

This finding highlight that the adoption of automated solutions significantly enhances system reliability**.** This is particularly crucial for critical infrastructures such as energy, water supply, and industrial production, where resilience and minimization of the human factor play a key role. Numerical values on the graph allow for a clear evaluation of automation efficiency at each level.

4.3 Practical Implications and Future Development

The results of the study emphasize that the full realization of renewable energy potential requires active infrastructure development, the deployment of intelligent control systems, energy storage technologies, and advanced weather forecasting. A critical component is the integration of artificial intelligence (AI) and machine learning (ML) systems to improve forecast accuracy and adapt to rapidly changing conditions.

According to analytical reports, investments in smart grids are expected to grow annually by 15-20% in the coming years, driven by the need to improve grid resilience and efficiency. However, the introduction of new technologies still faces major challenges, including the high cost of modernization**,** regulatory restrictions, and the need for standardization**.**

The use of big data and AI-based solutions enables more accurate forecasting of renewable generation, loss reduction, and improved reliability. In particular, ML algorithms applied to predictive analysis of equipment conditions and weather data can enhance management efficiency by 25-30% [15]. In summary, the models and systems developed and tested in this study demonstrate strong potential for practical implementation. The integration of intelligent management systems, energy storage, and forecasting technologies can significantly increase the share of renewable energy in total consumption, reduce losses, and ensure reliable grid operation under conditions of high generation variability.

5 CONCLUSIONS

This article presented a comprehensive study of modern methods and technologies aimed at modernizing energy systems**,** with a particular focus on the integration of renewable energy sources and the development of smart grids. Within the research framework, models of solar and wind generation**,** energy storage systems, and automated control systems were designed and tested, providing an up-to-date picture of the potential and prospects for deploying these technologies.

The modeling analysis revealed that solar power plants during the summer period exhibit stable generation, with peak output around midday reaching 20 MW, consistent with both model predictions and real-world data. Wind generation, while more variable, demonstrated an integration potential of

12.8 MW when supported by storage and control systems, confirming its importance for sustainable energy systems.

The practical value of the study was further confirmed through the performance of storage systems: the introduction of batteries enabled renewable utilization levels of up to 85%, a significant reduction in energy losses, and improved overall system reliability. The weather condition analysis showed that renewable efficiency is highly sensitive to meteorological factors, highlighting the need for advanced forecasting technologies and adaptive management systems.

Optimization methods, including genetic algorithms and dynamic programming, were successfully applied to develop strategies for minimizing losses and balancing energy flows. This led to a 25% reduction in losses and a 30% increase in renewable utilization.

Automation and monitoring models demonstrated that higher levels of system automation significantly reduce failure probability-from 3-4% down to 1.5%, thereby enhancing reliability and resilience. Visualization techniques, such as graphs, heat maps, and diagrams, provided clear insights into generation dynamics, battery charge levels, and regional distribution patterns.

In conclusion, the adoption of intelligent technologies, energy storage systems, and forecasting tools is the key to building an efficient and sustainable energy future. The models and methods developed within this study confirm their practical applicability and open new prospects for further research and real-world implementation.

Future development directions include the integration of artificial intelligence, machine learning, and big data analytics to improve forecasting accuracy, automate operations, and optimize grid performance. In the context of global climate change and the urgent need to reduce environmental footprints, such approaches are becoming an integral part of modern energy policy.

The results of this research confirm that modern technological solutions can significantly enhance the efficiency, reliability, and environmental security of energy systems through the integration of renewable energy sources and smart management technologies.

REFERENCES

[1] International Energy Agency (IEA), Renewables 2021: Analysis and Forecasts, IEA Publications, 2021.

[2] International Renewable Energy Agency (IRENA), Global Renewables Outlook 2020, IRENA Publications, 2020.

[3] European Parliament, “Energy transition in the EU - Towards a climate-neutral economy: European Green Deal and renewable energy policies,” European Parliamentary Research Service, Brussels, Belgium, Dec. 2023, [Online]. Available: https://www.europarl.europa.eu/RegData/etudes/BRIE/2023/754623/EPRS_BRI(2023)754623_EN.pdf.

[4] E. B. Saitov, “Renewable energy development in Uzbekistan: Current status, problems and solutions,” E3S Web of Conferences, vol. 216, p. 01134, 2020, [Online]. Available: https://doi.org/10.1051/e3sconf/202021601134.

[5] M. K. Bakhadyrkhanov, Kh. M. Iliev, S. A. Tachilin, S. S. Nasriddinov, and B. A. Abdurakhmanov, “Impurity photovoltaic effect in silicon with multicharge Mn clusters,” Applied Solar Energy, vol. 44, no. 2, pp. 132-134, 2008, [Online]. Available: https://doi.org/10.3103/S0003701X08020151.

[6] E. B. Saitov and U. M. Akhmedov, “Tracking maximum power point of photovoltaic modules,” AIP Conference Proceedings, vol. 2789, p. 060005, 2023, [Online]. Available: https://doi.org/10.1063/5.0145470.

[7] E. B. Saitov and T. B. Sodiqov, “Modeling an autonomous photovoltaic system in the MATLAB Simulink software environment,” AIP Conference Proceedings, vol. 2432, p. 020022, 2022, [Online]. Available: https://doi.org/10.1063/5.0089914.

[8] D. A. Elalfy, E. Gouda, M. F. Kotb, V. Bureš, and B. E. Sedhom, “Comprehensive review of energy storage systems technologies, objectives, challenges, and future trends,” Energy Strategy Reviews, vol. 54, p. 101482, 2024, [Online]. Available: https://doi.org/10.1016/j.esr.2024.101482.

[9] L. Ai Wong, V. K. Ramachandaramurthy, P. Taylor, J. B. Ekanayake, and S. L. Walker, “Review on the optimal placement, sizing and control of an energy storage system in the distribution network,” Journal of Energy Storage, vol. 21, pp. 489-504, 2019, [Online]. Available: https://doi.org/10.1016/j.est.2018.12.015.

[10] N. Zikrillayev et al., “A software package for determining the optimal composition and parameters of a combined autonomous power supply system based on renewable energy sources,” AIP Conference Proceedings, vol. 2432, p. 020021, 2022, [Online]. Available: https://doi.org/10.1063/5.0090460.

[11] E. B. Saitov, “Optimal model for additional operation of the storage system for photovoltaic wind power plants,” E3S Web of Conferences, vol. 220, p. 01080, 2020, [Online]. Available: https://doi.org/10.1051/e3sconf/202022001080.

[12] E. B. Saitov et al., “Networked interactive solar panels over the roof photovoltaic system (PVS) and its cost analysis at Tashkent State Technical University,” E3S Web of Conferences, vol. 216, p. 01133, 2020, [Online]. Available: https://doi.org/10.1051/e3sconf/202021601133.

[13] E. B. Saitov et al., “Study of solar radiation and wind characteristics in various regions of Uzbekistan,” E3S Web of Conferences, vol. 220, p. 01061, 2020, [Online]. Available: https://doi.org/10.1051/e3sconf/202022001061.

[14] I. Sapaev, E. Saitov, N. Zoxidov, and B. Kamanov, "Matlab-model of a solar photovoltaic station integrated with a local electrical network," IOP Conference Series: Materials Science and Engineering, vol. 883, p. 012116, 2020, [Online]. Available: https://doi.org/10.1088/1757-899X/883/1/012116.

[15] N. Zikrillayev, K. Ayupov, Z. Mamarajabova, I. Yuldoshev, E. Saitov, and I. Sabitova, "Adaptation and optimization of a photovoltaic system for a country house," E3S Web of Conferences, vol. 383, p. 04054, 2023, [Online]. Available: https://doi.org/10.1051/e3sconf/202338304054.